Applied Computer Systems
ISSN 2255-8691 (online)
ISSN 2255-8683 (print)
June 2024, vol. 29, no. 1, pp. 85–90
https://doi.org/10.2478/acss-2024-0011
https://content.sciendo.com

A Comparative Study of Various Machine Learning Techniques for Diagnosing Clinical Depression

Adegboye Adegboyega[1*], Anthony Agboizebeta Imianvan[2]
[1,2]*Department of Computer Science, University of Benin, Benin City, Edo State, Nigeria*

Abstract **– One of the major areas of machine learning application is in medical diagnosis. Machine learning algorithms can detect patterns in patients' data and generates a diagnosis based on those patterns. There are several machine learning classification algorithms each having different strengths and weaknesses, and this makes it difficult to determine the best one for classification problems. In this paper, machine learning techniques used to classify the clinical depression dataset are Fuzzy Logic, Neural Network, Neuro-Fuzzy System, and Genetic Neuro-Fuzzy System. A total of 134 clinical diagnosis first report depression datasets were used in arriving at prediction. The outcome of the experiment showed that the Genetic Neuro-Fuzzy model generated the best result with a prediction accuracy of 95 %, and cross-validation of 83.2 %. This shows that the model is robust and can make accurate prediction on new, unseen data. This research work will guide future researchers and practitioners to identify new directions for advanced development opportunities in using machine learning in depression diagnosis. It will help policymakers in the area of depression to make informed decisions, especially in the area of best machine learning technique for classification problem related to depression diagnosis. The research is limited to clinical depression diagnosis; future work could be expanded to compute the severity ranks of other depression-connected dysfunctions similar to diabetes, lungs, and cancer diseases.**

Keywords **– Clinical depression, fuzzy logic, genetic algorithm, neural networks.**

I. Introduction

Depression is a psychological ailment that can affect personality irrespective of sex, race, and age [1]–[3]. It is a significant contributor to the global disease burden [4]. In 2014, the World Health Organization (WHO) designated depression as the second principal reason for suicide in individuals aged 15 to 29 [5]. Statistical data reveal an 18.4 % increase in the overall estimated number of people experiencing depression between 2005 and 2015 [6]. As of 2015, the worldwide prevalence of depression was approximately 4.4 %, taking place more in females (5.1 %) compared to males (3.6 %) [6]. The prevalence of depression exhibits variations across different age groups, peaking in mature adulthood between the ages of 55–74, with estimated rates exceeding 7.5 % in females and over 5.5 % in males [6]. Currently, it is approximated that around 280 million people worldwide are living with depression [7]. The symptoms of depression encompass a range, including feelings of fatigue, loss of concentration or desire, a sense of responsibility or low self-confidence, disrupted sleep or need to eat, persistent sadness, and difficulties with concentration [8]. Due to the overlap of these symptoms, depression is often prone to misdiagnosis [9], [10]. Over the years, different types of machine learning techniques have been used in various forms to diagnosing depression with each technique generating different prediction accuracy. This has led to a persistent debate amongst researchers, which is the best machine learning technique for classification. While it is true that the machine learning classification algorithm with the highest classification accuracy should be regarded as the best, it could be argued that the nature of the data, training time, training, and testing data sample size are significant factors in determining the accurateness of the model. Therefore, to determine the best technique for a classification problem, the same data, training, and test sample size should be applied across each technique. In this paper, we make use of Fuzzy Logic, Neural Network, Neuro-Fuzzy System, and the Genetic Neuro-Fuzzy System in classifying clinical depression datasets.

II. Review of Related Studies

Several research studies and models have been implemented for diagnosing depression [9]–[13]. In a study documented in [9], a Soft Computing Model for Depression Prediction was developed. The authors utilised an Adaptive Neuro-Fuzzy System, resulting in a model with enhanced precision and a decreased system blunder rate. However, it is noteworthy that the model lacked the incorporation of feature extraction and selection. Another investigation, detailed in [14], involved the application of an Artificial Neural Network (ANN) Model for predicting depression in the aged populace within a Kolkata slum, India. This model exhibited superior accuracy in predicting results, proficient learning capabilities through unsupervised learning, and a reduction in system error rates. Nevertheless, similar to the previous study, the implementation of a feature extraction and selection module was absent. Similarly, Osubor and Egwali, in their work [10], designed a neuro-fuzzy system for diagnosing postpartum depression disorder. The model exhibited a higher level of result precision

[*] Corresponding author's e-mail: akanbi2090@yahoo.co.uk
Article received 2024-01-09; accepted 2024-07-26

and a lower system blunder rate, but like the previous study, it lacked a feature extraction module. In the study by Yoshihiko et al., documented in [15], the authors predicted a depressed mood by leveraging self-reported past records through Recurrent Neural Networks. Despite the model demonstrating heightened accuracy in result prediction, adept proficiency in unsupervised learning, and a reduced system blunder rate, the authors did not include a feature extraction and selection module. A similar model was designed in [11], the model was designed by means of an Adaptive Neuro-Fuzzy Inference System and it was capable of generating high accuracy, learning capability by means of unsupervised learning and producing a reduction in system error rate, but this model had a shortfall of not incorporating feature extraction and selection. In [16], a Feed Forward Neural Network and Radial Basis Function Neural Network were utilised to model depression data. Although the model did not incorporate feature extraction and selection, it had a high accuracy of result prediction and the capability to learn through unsupervised learning. In [17], a Genetic Algorithm and Adaptive Neuro-Fuzzy System were exploited to grade depression. The model generated excellent results in terms of grading depression, but a huge drawback of their model was that the GA was only used to select a subset of the symptom base and this would hamper the system from operating to its optimal. The study [18] makes use of Multi-kernel Support Vector Machines for the identification of a depressed person from social media data. Although the system had a reduced error rate in identifying the depressed people, it had the following drawbacks: lack of feature extraction and selection on symptom base, poor performance due to kernel introduction for multivariate, lack of higher prediction power on training due to a single optimal solution, not fast in training and testing, higher algorithmic complexity, extensive memory requirements, and consumption. In [19], the detection of major depressive disorder via vocal acoustic analysis and machine learning was presented. The research findings indicate that employing machine learning classifiers with vocal acoustics features holds significant promise for detecting major depressive disorder. However, further research is required to validate the authenticity of vocal acoustics in the diagnosis of depression. It is worth noting that the speech recordings were obtained in typical settings, during routine medical evaluations for psychiatric patients. A limited sample was used; however, an additional test with a larger sample was essential in order to confirm the research findings. The study [20] presented predicting the psychological health of prisoners by the use of Artificial Neural Network. Neural Network and SPSS-2 were used. The outcome of the study indicated that the system was capable of predicting the mental health of prisoners. The major limitation of the system is that feature selection and feature extraction were not used to extract relevant data from the set of data used for training and evaluating the system.

III. Machine Learning

A. Fuzzy Logic

Fuzzy logic was initiated by Lotfi Zadeh in 1965 as an approach for computing the degree of truth, which is different from the conventional Boolean logic. It handles logical reasoning with vagueness and imprecision in statements [21]. The fuzzy inference system is made of four components namely: fuzzification, rule layers, inference engine, and defuzzification.

Fuzzification: In this phase, the inputs into the fuzzy system are converted into fuzzy values. The membership function is used to convert the inputs.

Rule Layer: The rule layers consist of series of rules to produce the required output.

Inference Engine: The inference engine computes the aggregation of the rules triggered in the course of generating the required output.

Defuzzification: The defuzzification layer converts the fuzzy values into crisp output.

Figure 1 depicts the structural design of a fuzzy logic system.

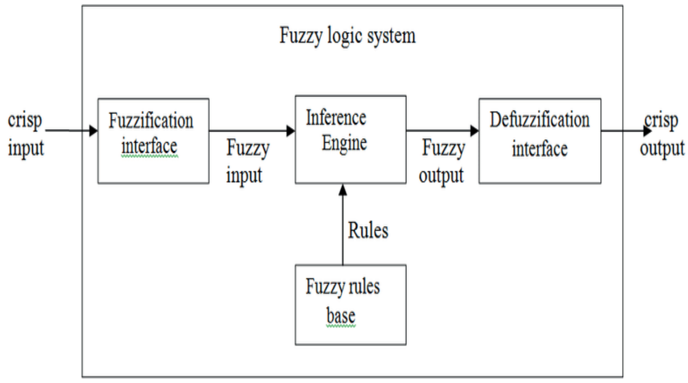

Fig. 1. Architecture of a fuzzy logic system [21].

B. Artificial Neural Network

An Artificial Neural Network is a structured assembly of nodes, inspired by the arrangement of neurons in the human brain. An ANN model typically consists of three interconnected layers: the output layer, the hidden layer, and the input layer. Each layer performs various functions, including multiplication, summation, and activation. In the input layer, each neuron is assigned a weight and undergoes multiplication with the input value. The hidden layer then computes the summation of all neurons from the input layer. Finally, the output layer generates the output by applying an activation function to the inputs received from the hidden layer. Figure 2 illustrates the architectural layout of an ANN network.

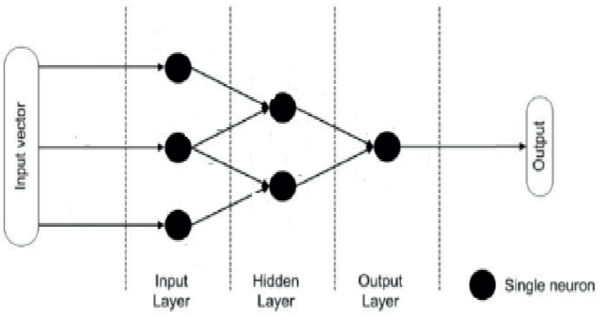

Fig. 2. Architecture of an ANN.

C. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is composed of Fuzzy Logic and ANN. It combines the advantages of both systems to produce a hybrid system that has a computational and explanative power. It comprises six levels.

Layer 1: This is the input level.

Layer 2: This is the membership function level which maps the input into a fuzzy set.

Layer 3: This is the rule level, and all preceding nodes from Level 2 are computed here.

Layer 4: This is the normalisation level; all inputs from Level 3 are normalised here.

Layer 5: This is the aggregation level.

Layer 6: This is the output level, and it produces the output of the entire system.

Figure 3 shows the structural design of an ANFIS.

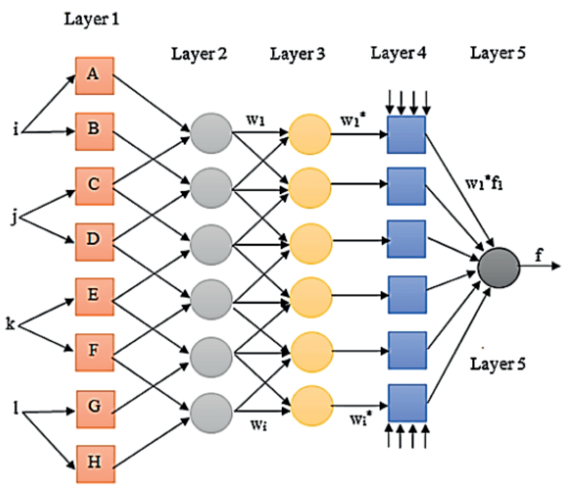

Fig. 3. Architecture of an ANFIS.

D. Genetic Algorithm

A genetic algorithm is a search exploratory that draws inspiration from Charles Darwin's natural selection theory. This algorithm imitates the natural selection process, where the well-adapted entities are selected to generate the subsequent generation of offspring. The genetic algorithm comprises five phases.

Initial population: It is the first set of the individual. An individual is made of chromosomes, which comprise the gene.

Fitness function: The fitness function establishes how fit an individual is when compared to others in the population.

Selection: This is the process of selecting fitted individuals from the population.

Crossover: This is the process of creating new offspring.

Mutation: This process subjects a random offspring in the population to gene mutation.

IV. Methodology

The dataset employed in this research was gathered from the Federal Medical Centre in Owo, Ondo State. Examination information was compiled by hand from patients' health analysis cards, supplemented by reflective analytical details obtained from seasoned psychiatrists at the Federal Medical Centre in Owo. A skilled psychiatrist at the same medical centre confirmed and validated the data. The dataset, comprising 22 columns, includes the first 21 columns representing criteria (such as Guilt, Pessimism, Sense of Failure, etc.) for identifying clinical depression, and the last column indicates the diagnostic result. An aggregate of 134 datasets was thoroughly scrutinised by the author in addition to other skilled psychiatrists at the health centre to reach diagnostic predictions. There, the Beck Depression Inventory was employed for diagnosing depressive episodes. Four different techniques, namely Fuzzy Logic, Neural Network, Neuro-Fuzzy System, and the Genetic Neuro-Fuzzy System, were implemented to diagnose clinical depression using the dataset obtained from the medical centre. Specifically, in the case of the Genetic Neuro-Fuzzy System, the Beck Inventory scale was translated into a mathematical equation, and this equation was the objective function for the Genetic Algorithm. Each model was trained using Matrix Laboratory (MatLab) for 30 epochs using the same 94 training samples and tested the same 40 test samples.

V. Results and Discussion

The recital of each system was evaluated by means of four assessments, namely, Confusion Matrix, Sensitivity, Specificity, and Classification Accuracy. Forty test cases were used to evaluate each model. The set of values obtained is presented in Table I.

TABLE I

Confusion Matrix for Fuzzy Logic

Test Result	Positive	Negative	Total
Positive	18 (TP)	3 (FP)	21
Negative	1 (FN)	18 (TN)	19
Total	19	21	40

Sensitivity = TP/TP+FN = 0.9473684210526315.

Specificity = TN/TN+FP = 0.8571428571428571.

Positive Predictive Value (PPV) = TP/TP+FP

= 0.8571428571428571.

Negative Predictive Value (NPV) = TN/TN+FN

= 0.9473684210526315.

False Negative Rate = FN/TP+FN

= 0.05263157894736842.

False Positive Rate = FP/TN+FP = 0.14285714285714285.

False Discovery Rate = 1−PPV = 0.1428571428571429.

False Omission Rate = 1−NPV = 0.052631578947368474.

Critical Success Index = TP/TP+FN+FP

= 0.8181818181818182.

Accuracy = TP+TN/TP+TN+FN+FP = 0.9.

From the above calculation, the system predictive accuracy is 90.0 %.

TABLE II
CONFUSION MATRIX FOR ARTIFICIAL NEURAL NETWORK

Test Result	Positive	Negative	Total
Positive	19 (TP)	2 (FP)	20
Negative	1 (FN)	18 (TN)	10
Total	20	20	40

Sensitivity = TP/TP+FN = 0.95.

Specificity = TN/TN+FP = 0.9.

Positive Predictive Value (PPV) = TP/TP+FP

= 0.9047619047619048.

Negative Predictive Value (NPV) = TN/TN+FN

= 0.9473684210526315.

False Negative Rate = FN/TP+FN = 0.05.

False Positive Rate = FP/TN+FP = 0.1.

False Discovery Rate = 1−PPV = 0.09523809523809523.

False Omission Rate = 1−NPV = 0.052631578947368474.

Critical Success Index = TP/TP+FN+FP

= 0.8636363636363636.

Accuracy = TP+TN/TP+TN+FN+FP = 0.925.

From the above calculation, the system predictive accuracy is 92.5 %.

TABLE III
CONFUSION MATRIX FOR ADAPTIVE NEURO-FUZZY SYSTEM

Test Result	Positive	Negative	Total
Positive	20 (TP)	2 (FP)	22
Negative	1 (FN)	17 (TN)	18
Total	21	19	40

Sensitivity = TP/TP+FN = 20/20+1 = 0.95.

Specificity = TN/TN+FP = 17/17+2 = 0.895.

Positive Predictive Value (PPV) = TP/TP+FP = 20/20+2

= 0.909.

Negative Predictive Value (NPV) = TN/TN+FN = 17/17+1 = 0.895.

False Negative Rate = FN/TP+FN = 1/20+1 = 0.048.

False Positive Rate = FP/TN+FP = 2/17+2 = 0.105.

False Discovery Rate = 1−PPV = 1-0.909 = 0.091.

False Omission Rate = 1−NPV = 1-0.895.

Critical Success Index = TP/TP+FN+FP = 20/20+1+2

= 0.87.

Accuracy = TP+TN/TP+TN+FN+FP = 20+17/20+1+2+17 = 0.925.

The value shown above indicates that the system predictive accuracy is 92.5 %.

TABLE IV
CONFUSION MATRIX FOR GENETIC NEURO-FUZZY SYSTEM

Test Result	Positive	Negative	Total
Positive	20 (TP)	1 (FP)	21
Negative	1 (FN)	18 (TN)	19
Total	21	19	40

Sensitivity = TP/TP+FN = 0.9523809523809523.

Specificity = TN/TN+FP = 0.9473684210526315.

Positive Predictive Value (PPV) = TP/TP+FP

= 0.9523809523809523.

Negative Predictive Value (NPV) = TN/TN+FN

= 0.9473684210526315.

False Negative Rate = FN/TP+FN

= 0.047619047619047616.

False Positive Rate = FP/TN+FP = 0.05263157894736842.

False Discovery Rate = 1−PPV = 0.04761904761904767.

False Omission Rate = 1−NPV = 0.052631578947368474.

Critical Success Index = TP/TP+FN+FP

= 0.9090909090909091.

Accuracy = TP+TN/TP+TN+FN+FP = 0.95.

From the above calculation, the system predictive accuracy is 95.0 %.

Upon comparison, the Genetic Neuro-Fuzzy System exhibited the peak of classification accuracy. This superiority can be attributed to the utilisation of feature selection and extraction on the dataset prior to training. Additionally, it was noted that both the artificial neural network and the neuro-fuzzy system achieved identical prediction accuracy of 92.5 %, while the fuzzy system displayed the lowest prediction accuracy at 90 %. The experimental results underscore the significance of applying feature extraction and selection to enhance the prediction performance of machine learning algorithms.

TABLE V

PARAMETERS USED IN THE GA

S/N	Research Method	Genetic Algorithm
1.	Population Size	114
2.	Number of Generation	50
3.	Probability of Crossover	10 %
4.	Probability of Mutation	10 %

Table V shows the population size, generation through which the dataset was processed, the crossover and mutation function.

Table VI shows the partitioning of the dataset; 70 % of the dataset was used for training the model, while 20 % of the dataset was used for testing and the remainder used for validating the model.

TABLE VI

DATA PARTITION

S/N	Data partition set	Records	Percentage
1.	Training Set	94	70 %
2.	Test Set	20	20 %
3.	Validation Set	20	20 %
4.	Total	134	100 %

Calculation of Cross-validation (Steps)

1. The data were partitioned into five groups, four groups contained 26 record each ((20 % of 134), while one group contained 20 records (remaining records);
2. The model was trained on the four groups that contained 26 records each (a total of 104 records);
3. Step 2 was repeated for each group, so each group was used as a test set once;
4. The accuracy of each iteration was calculated;
5. The accuracy across all five iterations was calculated.

The accuracy for each iteration is as follows:

- Iteration 1: 85 %;
- Iteration 2: 80 %;
- Iteration 3: 82 %;
- Iteration 4: 88 %;
- Iteration 5: 81 %.

The average accuracy across all five iterations is as follows:

Accuracy = (85 + 80 + 82 + 88 + 81) / 5 = 83.2 %.

This is the cross-validation result, indicating that

1. The model's average accuracy is 83.2 % when trained and tested on different subsets of the data;
2. The model is performing well, with an average accuracy of 83.2 % across all five iterations;
3. The model is generalising well to new, unseen data (since it is tested on a different subset each time);
4. There is some variation in performance across iterations (as seen from the individual accuracies: 85 %, 80 %, 82 %, 88 %, 81 %), but the average accuracy is a good representation of the model's overall performance;
5. The model is robust and can make accurate predictions on data it has not seen before, which is a key goal in machine learning.

VI. CONCLUSION AND FUTURE SCOPE

There are a large number of machine learning algorithms available and most researchers often choose a machine learning algorithm for classification based on trial and error. However, choosing an optimal machine learning algorithm for any classification problem depends on the nature of the data, training, and testing data sample size, and training time. Therefore, to determine the best technique for a classification problem, the same data, training, and test sample size should be applied across each technique. In this paper, we used Fuzzy Logic, Neural Network, Neuro-Fuzzy System, and Genetic Neuro-Fuzzy System to classify clinical depression datasets. The outcome of the experiment showed that the Genetic Neuro-Fuzzy System had the highest classification accuracy.

ACKNOWLEDGMENT

Sincere appreciation goes to the staff and management of Federal Medical Centre, Owo, Ondo State.

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Adegboye Adegboyega holds a Master and Bachelor of Science in Computer Science, Master of Business Administration and Higher National Diploma in Electronics Engineering. He is a Member of the Council for the Regulation of Engineering Practice in Nigeria (COREN), Computer Professional Registration Council of Nigeria (CPN) and Nigeria Computer Society (NSC). His current research focuses on HealthCare Delivery System. He has organised and also published articles in national, international peer-refereed journals, conferences, book chapters, and presented papers. He taught undergraduate level courses in Management Information Systems and Computing. He is a Visiting Lecturer at other higher education institutions. He serves as a Reviewer and Member of the Editorial Board of highly reputable journals across the globe. He is an Editor-in-Chief of the International Journal of Sustainable Development Research, Lead Guest Editor of the American Journal of Health Research and Member of some committee within and outside the higher institution. His academic and professional career achievement includes successful accomplishments of Computer Science Department approval, accreditation, and mobilization of students for the National Youth Services Corps (NYSC). He participated in curriculum development and vocational enterprises. He rebranded course curriculum and program(s) to add value and reorient them to solve community and global problems in addition to a fundamental understanding of the concerned program. He is a recipient of the prestigious Fulbright grant award.
E-mail: adegboyega.adegboye@physic.uniben.edu
ORCID iD: https://orcid.org/0000-0002-5602-1009

Anthony Agboizebeta Imianvan is a Professor of Computer Science at the Faculty of Physical Sciences, University of Benin. He received his B.Sc and M.Sc degrees in Computer Science from the University of Benin, Benin City, Nigeria in 1993 and 1998, respectively. He obtained PhD degree in Computer Science from the Federal University of Technology, Akure, Nigeria in 2009. He is a Member of the Nigeria Computer Society and Member of the Computer Professional Registration Council of Nigeria. His current research is on artificial intelligence, knowledge engineering, soft computing, intelligent agents, networking, algorithms and biomedical computing.
E-mail: tonyvanni@uniben.edu
ORCID iD: https://orcid.org/0009-0008-7054-2610